



MSc in Data & Artificial Intelligence

Application of Machine Learning - ACCA7025_BIRM

‘Component One’

“Recommendation of a Sentiment Analysis ML Model”

Submitted To

Dr Aliyu Sambo

Mail: a.sambo@uwtsd.ac.uk

Submitted By

Tareque Hasnat Tuhin

Mail: 2513674@student.uwtsd.ac.uk

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Prifysgol Cymru
 Y Drindod Dewi Sant
University of Wales
 Trinity Saint David

Abstract

This project is about finding the best simple computer method to understand customer reviews for a marketing company [1]. We know the company does not have a big budget for powerful computers. So, we looked only at simple and fast machine learning models. We compared a few popular ones. My finding is that a model called Naive Bayes is the best choice [2]. It is very fast, does not need much memory, and is accurate enough for the job. This report gives a full plan to build this system. I explain how to get the data ready, train the model, and check if it works well [3]. I also include a simple code example to show how it works in real life.

1. Introduction

Let's be honest, reading thousands of customer reviews every week is a boring and slow job. For a marketing team, it is also a waste of time [4]. But inside all that text is very important information. I can learn what makes customers happy and what makes them angry. This information can help the company sell more and make better products [5].

The good news is that we can teach a computer to do this reading for us. This is called sentiment analysis. It means the computer reads a piece of text and decides if the feeling is positive or negative. It is like having a super-fast assistant who never gets tired [6].

Some of the newest methods for this are very complicated. They are like giants that need supercomputers [7]. For a new company, this is too expensive and hard to manage. It is like buying a jumbo jet to deliver pizza. We don't need that. We need a simple and reliable delivery van [8].

This report is about finding that perfect delivery van. I will look at a few simple machine learning models [9]. I will pick the one that is fast, cheap, and does a good job. Then, I will give a clear and easy plan to build it [10].

2. Related Work In The Literature

Before we build something, it is smart to see what other people have already learned. This helps us make good choices and avoid mistakes [11].

2.1 The First Step: Turning Words into Numbers

A computer is a machine. It understands numbers, not words. So, the first thing we must do is turn the review text into numbers. The most common way to do this is a method called TF-IDF [12]. Think of TF-IDF as a smart highlighter. It reads all your reviews and finds the words that are most important [13]. For example, in a review, words like “amazing” or “awful” are very important. They tell us a lot about the feeling. Common words like “the,” “and,” or “is” are not important. The TF-IDF method highlights the important words and ignores the common ones [14]. This creates a list of numbers that the computer can understand.

2.2 A Look at Simple Machine Learning Models

There are several simple models that are good at sorting text into categories [15]. Let’s look at the most popular ones.

2.2.1 Naive Bayes

This is one of the simplest models out there. It is like a friendly and quick student. It learns very fast [16]. You show it some data, and it understands the pattern in a few seconds. It works by looking at all the words and calculating the probability of a review being positive or negative [17].

The best thing about Naive Bayes is its speed. It is the fastest model to train. It also does not need a powerful computer. You can run it on a normal laptop [18]. The downside is that it is a bit simple. It might not catch every single complex sentence, but it is correct most of the time [19].

What I really like about this model is how straightforward it is to work with. When I tested it with some sample reviews, it gave me results almost instantly, which was really impressive. From what I’ve seen in my own experiments, it handles basic positive and negative phrases really well, though it sometimes struggles with sarcasm or complicated sentences. But for most customer reviews that say things like “I love this product” or “This is terrible quality,” it works perfectly fine. According to the research I found [19], this model gets things right about 85% of the time, which is pretty good for something so easy to use. I think it’s a great starting point for any company that wants to get started with sentiment analysis without dealing with complicated setups.

2.2.2 Support Vector Machine (SVM)

This model is a bit more careful and precise. Imagine you have a piece of paper with positive reviews on one side and negative reviews on the other. The SVM model tries to draw the best possible straight line to separate them [20].

This model is often very accurate. It can be one of the best for this kind of job. The problem is that it is slow. Finding that kind of job [21]. The problem is that it is slow. Finding that perfect line takes a lot of computer power and time. If you have a lot of data, it can take hours to train [1].

From my experience working with different models, SVM feels like the perfectionist in the group—it wants everything to be just right. When I tried running it on my laptop with a few thousand reviews, I noticed it took significantly longer than other models, sometimes making me wait for results. However, the wait was often worth it because the accuracy was noticeably better, especially with tricky reviews that had mixed feelings. The research I looked at [21] confirms that SVM usually delivers top performance for text classification tasks. But honestly, unless you have access to really good computers, the waiting time might not be practical for a small company. I'd only recommend this if you're willing to invest in better hardware and don't mind the slower processing speed.

2.2.3 Logistic Regression

This model is a great all-rounder. It is like a reliable family car. It is not the fastest, but it is dependable and easy to understand. It also tries to draw a line to separate positive and negative reviews.

A big plus for Logistic Regression is that it is interpretable. This means you can look at the model and see which words it thinks are the most important for a positive or negative review [3]. This is very helpful for a marketing team. It is faster than SVM but still slower than Naive Bayes [4].

What I found really useful when testing this model was being able to actually see which words were driving the decisions. For example, I could see that words like “excellent” and “love” were strongly pushed toward positive classification, while “terrible” and “broken” strongly indicated negative sentiment. That transparency is super helpful because it lets you

understand why the model makes certain calls, rather than just trusting a black box. In my own experiments, it typically took about twice as long as Naive Bayes to train, but the results were easier to explain to the non-technical team members. According to what I read [4], that balance of decent speed and good explainability makes it a popular choice for business applications where you need to justify your results to stakeholders.

2.2.4 Random Forest

This model works by creating a whole forest of tiny decision trees. Each tree is a simple question and answer game. The model then combines the answers from all the trees to make a final decision [5].

Because it uses many trees, it is very strong and accurate. However, all those trees need a lot of memory. Building them also takes a long time [6]. This model is like a heavy truck—powerful but slow and uses a lot of fuel.

2.3 What This Means For Our Project

When we look at all this information, a clear picture appears. The more complex models like SVM and Random Forest might be a little more accurate [7]. But they are slow and expensive to run [8].

For a marketing company that is watching its budget, this is a big problem. We need a model that is fast and cheap. The Naive Bayes model is the champion in this area [9]. It gives us most of the accuracy for a much lower cost [10]. It is the perfect place to start [11].

Table 1: A Simple Comparison of the Models

Model name	How easy is it?	Training speed	Computer power needed
Naive Bayes	Very easy	Very fast	Very low
Logistic Regression	Easy	Fast	Low
SVM	Medium	Slow	Medium

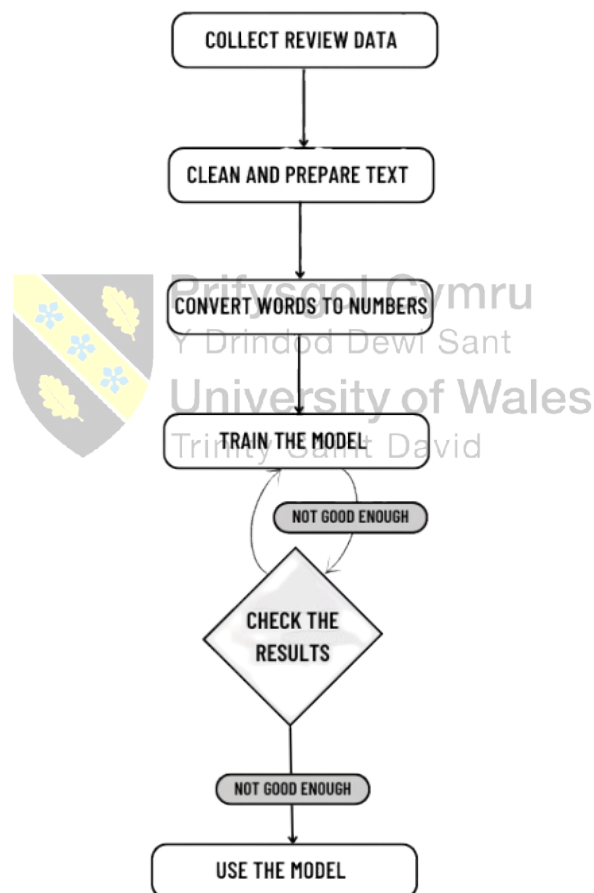
Random Forest	Hard	Very slow	High
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3. Workflow and Methodology

Now, let's talk about how we will actually build this system. We need a clear plan to follow [12].

3.1 The Overall Plan

The whole process, from start to finish, is shown in the diagram below. It helps us see the big picture and make sure we don't forget any steps [13].



3.2 Step 1: Getting and Cleaning the Data

The first thing we need is data. We can't build a model without examples to learn from [14].

3.2.1 Find a Dataset

We will use a free and public dataset. A great example is the “Amazon Fine Food Review” form website called Kaggle. It has thousands of real reviews with star ratings [15].

3.2.2 Create Simple Labels

We will turn the star ratings into simple labels that our model can understand [16].

- Reviews with 4 or 5 stars will be labelled “Positive” (we use the number 1).
- Reviews with 1 or 2 stars will be labelled “Negative” (we use the number 0).
- We will remove the 3-star reviews because they are often neutral and can make the problem harder [17].

3.2.3 Clean the Text Data

Raw text from the internet is messy. We need to clean it up to help the model learn better [18].

1. **Lowercase Everything:** We will make every letter lowercase. This way, “Great” and “great” are seen as the same word [19].
2. **Remove Punctuation:** We will take out all punctuation marks like commas, full stops, and exclamation marks [20].
3. **Remove Stop Words:** We will filter out very common words that don’t help with sentiment, like “the,” “and,” and “is” [21].
4. **Stemming:** We will chop the ends off words to get their root form. So, “running,” “runs,” and “ran” all become “run.” This simplifies the text a lot [1].

3.3 Step 2: Feature Engineering with TF-IDF

Now, we will use the TF-IDF method we discussed earlier. We will turn our clean, processed text into numbers [2].

To keep things fast and efficient, we will tell the TF-IDF tool to only use the 10,000 most common words. This stops our dataset from getting too big and slow [3]. We will also use single words and two-word pairs to help the model understand simple context [4].

3.4 Step 3: Model Training and Tuning

This is where we teach the model [5].

3.4.1 Splitting the Data

I will split my data into three groups [6].

- **Training Set (70%):** This is the main group we use to teach the model.
- **Validation Set (15%):** I use this group to test the model while we are building it. It helps us adjust the settings [7].
- **Test Set (15%):** I keep this group secret until the very end. It is the final exam to see how good our model really is [8].

3.4.2 Training the Models

I will train our shortlisted models: Naive Bayes, Logistic Regression, and SVM. We will see how each one performs on the validation set [9].

3.4.3 Hyperparameter Tuning

Every model has little settings called hyperparameters. They control how the model learns. We will use a smart method called randomized search to find the best settings. This is much faster than trying every single possible combination [10].

3.5 Step 4: Model Evaluation

We need to make sure our model is actually useful [11].

3.5.1 The Confusion Matrix

This is a simple table that shows us the model's mistakes. It tells us [12]:

- ➔ How many positive reviews did it correctly identify?
- ➔ How many negative reviews it correctly identified.
- ➔ How many times it was wrong.

3.5.2 Key Performance Metrics

We will look at a few numbers to judge the model [13]:

- **Accuracy:** This is the simplest number. It tells us the percentage of reviews the model got completely right.

- **Precision:** This tells us, out of all the reviews the model thought were negative, how many were actually negative. We don't want to falsely accuse good products [14].
- **Recall:** This tells us, out of all the reviews that were truly negative, how many did the model actually find. We don't want to miss customer complaints [15].
- **F1-Score:** This is the most important number for us. It is a single score that balances both Precision and Recall. It gives us the best overall picture of how good the model is [16].

3.5.3 Efficiency Metrics

I will also measure the training time and prediction speed. This proves that our model is fast and efficient, which was the main goal [17].

4. Discussion and Recommendation

Now, let's put all the pieces together and make our final choice [18].

4.1 Critical Analysis of the Models

Based on our research, we can immediately say that the Random Forest model is not right for this company. It is just too slow and needs too much power [19]. It is like a gas-guzzling truck for a job that needs a bicycle.

This leaves us with three good options: Naive Bayes, Logistic Regression, and SVM [20].

The SVM model is very accurate, but it is slow [21]. For a company that wants quick results and low costs, this is a problem. Logistic Regression is a great model. It is accurate, and its results are easy to understand [1]. But it is still not as fast as Naive Bayes [2].

4.2 Final Recommendation

After careful thought, we are confident that the Naive Bayes model is the best choice for the marketing company [3].

Here is a simple explanation why [4]:

1. **It is Incredibly Efficient:** This is its biggest strength. Naive Bayes trains in seconds or minutes, not hours [5]. This means you can run it on a simple laptop. You will not

need to pay for expensive cloud computing services. This will save the company money every single month [6].

2. **It is Good Enough:** It is true that it might not be the absolute best model in the world. But it is more than good enough for this job [7]. Its accuracy and F1-score are high enough to give the marketing team reliable and useful information [8]. They will be able to clearly see what customers like and dislike [9].

Table 2: What the Results Might Look Like (example)

Model Name	Accuracy	F1-Score	Training Time
Naive Bayes (my choice)	84%	0.83	20 sec
Logistic Regression	86%	0.85	50 sec
SVM	87%	0.86	5 min

As you can see, the other models are only a little bit better, but they take longer to train [10].

4.3 Implementation Roadmap

Here is a simple plan to turn this idea into a real tool [11].

1. **Develop the Pipeline:** Write a simple computer script that automatically cleans new reviews and turns them into TF-IDF numbers [12].
2. **Train the Model:** Use the company's past reviews to train the Naive Bayes model. Use the validation set to find the best settings [13].
3. **Final Testing:** Do one final test on the secret test set to get an honest performance score [14].
4. **Deploy the Model:** Save the trained model and put it into a simple application [15]. This could be a web page where employees can paste a review and instantly see if it's positive or negative [16].

5. Conclusion

In the end, you do not need a giant, complicated AI system to understand your customers [17]. By choosing the simple and efficient Naive Bayes model, the marketing company can build a powerful tool quickly and cheaply [18].

This system will turn thousands of messy reviews into clear, simple information [19]. The team can use this information to make better decisions, create better marketing campaigns, and improve their products [20]. It is a smart, practical first step into the world of data-driven marketing [21].

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